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Underwater Image Enhancement – An Accessible Solution

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***Abstract*—Underwater optical images are insufficient for visual examination or analysis due to their poor colour representation, low contrast, and excessive noise levels. This project suggests a novel method of underwater image improvement that includes colour correction, image defogging/dehazing, image denoising, and object recognition in order to overcome these difficulties.**

The procedure relies on the image_dehazer python library for dehazing, the fastNlMeansDenoisingColored function of OpenCV for denoising, and the Google vision API for object detection. Based on the input image, a filter matrix is created to correct the colour by adjusting the hue and normalising the red, green, and blue channel intensities.

The suggested technique is put into practice using a flask API that is hosted on the internet and usable on low-end computers and mobile devices. In contrast to existing approaches, this technology is highly effective and appropriate for a variety of underwater imaging applications because it does not rely on machine learning or training models.

This research presents an effective method for improving underwater images, suitable for various imaging applications. The sample size of the images used was 890 (Large Scale Underwater Image Dataset). The temporal efficiency of this code is significantly influenced by the dimensions of the input image and the intricacy of the filter matrix. It has potential use in submarine operations for defense purposes such as surveillance and monitoring. The proposed method produces high-quality results while being accessible and cost-effective.

Keywords—Underwater, image processing, denoising, dehazing, color correction.

I. INTRODUCTION

Underwater imaging is a complex task because of light attenuation, absorption, and scattering in water. These conditions result in low-contrast and noisy images, making it difficult to extract useful information. Therefore, developing efficient methods to denoise underwater images is crucial to improve their quality and visual appearance.

This paper proposes a new method for denoising underwater images that combines the single-image haze removal method with the dark channel prior (DCP) algorithm and the Fast Denoising Colored Guided Image Filter (FDCGF). The DCP algorithm calculates the transmission map, which quantifies the amount of haze in the image, and then employs it to remove haze and improve image contrast.

The proposed method involves several steps: converting the input image to grayscale, calculating the dark channel of the grayscale image, estimating the transmission map using the DCP algorithm, removing haze from the image based on the estimated transmission map, and finally, denoising the image using the Non-local Means (NLM) algorithm.

The FDCGF algorithm is a fast and efficient method for denoising colored images. The technique employs a guided filter to eliminate noise while maintaining the image's sharp edges and small details. The guided filter is a generalisation of the bilateral filter in which the guidance signal is the input image itself. This allows the filter to adapt to the local structures in the image and achieve better denoising performance.

The DCP algorithm is based on the observation that the dark channel of outdoor images is very low in regions with haze. It calculates the transmission map by assuming that the image's minimal value in a local window corresponds to the image's haze-free parts. On the other hand, the NLM algorithm averages pixels in a local neighborhood based on the similarity between the pixels measured using a weighted average of their intensities.

The suggested method is tested on an underwater image dataset, and the findings reveal that it beats existing methods in terms of objective measures as well as visual quality. The proposed technology has the potential to be beneficial for a variety of underwater imaging applications, including underwater surveillance, marine biology, and oceanography.

The paper's structure includes a literature review of existing methods for denoising underwater images, a detailed description of the proposed method, experimental results, and a discussion of future research directions. [1]–[5][6]

II. ISSUES AND CHALLENGES

Since a decade ago, underwater image processing has received substantial attention due to the physical characteristics of water and its state.

Exercises in identifying and recognising objects underwater have created new challenges. These activities have resulted in considerable issues because of the effects of light absorption and diffusion.

Light attenuation

As light travels through water, it is absorbed and scattered, which results in light attenuation. As a result, there may be colour distortion, less contrast, and poorer imagequality. Light attenuation in water is calculated using the Beer-Lambert Law, which shows an exponential decrease in light intensity with depth. The Beer-Lambert Law can be used to estimate the intensity of light at a

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particular depth and to determine the minimal quantity of light needed to capture a picture at a certain depth, according to a study by Kirk.[7]

$$I = I_0 * e^{(-k*d)} \quad (1)$$

where I is the intensity of the light after it has traveled through a distance d, I_0 is the initial intensity of the light, k is the absorption coefficient of the medium, and the mathematical constant e is roughly 2.718 in value.

A. *Water turbidity*

Due to light scattering and reduced contrast, water turbidity can affect visibility and image quality. The Mie theory, which takes into consideration the size and concentration of particles in the water, can be used to describe the amount of light dispersed by turbid water. "Mie theory can be used to estimate the scattering of light in water due to particles, which can help predict the visibility and image quality in turbid water," claims a study by Mobley.[8]

$$Q_{ext}=[(2/x^2) * |B(x)|^2] * [(2x^2/(x^2 + 1)^2) + (2/x^2) * |C(x)|^2] \quad (2)$$

whereQ_{ext} is the extinction efficiency, x is the size parameter defined as the ratio of the particle diameter to the wavelength of light, B(x) and C(x) are the Mie coefficients which depend on the refractive index of the particle and the medium, and $|B(x)|^2$ and $|C(x)|^2$ represent the magnitudes of the coefficients squared.

B. *Color distortion*

The selective absorption of light by water and the scattering of light by water-borne particles result in colour distortion in underwater photographs. The White Balance Equation, a mathematical formula, is used to modify the colour balance of photos to take into account the selective absorption of light in underwater photography. The White Balance Equation can be used to alter the colour balance of underwater photographs and correct for colour distortion brought on by water absorption, according to a study by Kawaguchi.[9]

$$R\_corr = R / R\_w * R\_gw \quad (3)$$

$$G\_corr = G / G\_w * G\_gw \quad (4)$$

$$B\_corr = B / B\_w * B\_gw \quad (5)$$

where R_corr, G_corr, and B_corr are the corrected red, green, and blue channels of the image, R, G, and B are the original red, green, and blue channels of the image, R_w, G_w, and B_w are the white balance values of the image, and R_gw, G_gw, and B_gw are the gains applied to the image.

C. *Backscatter*

The reflection of light by particles and other suspended objects in the water is what causes backscatter in underwater photographs. Images may become blurry and lose contrast as a result of this. The Volume Scattering Function (VSF), which characterises the scattering of light by particles as a function of angle and wavelength, is the mathematical formula for backscatter in water. "The VSF can be used to estimate the amount of backscatter in water, which can help predict the image quality and visibility in different water conditions," claims a study by Mobley.[8]

$$b(\theta) = C * ((1 - g^2) / (4\pi)) * P(\theta) \quad (6)$$

where C is a constant related to the concentration and size distribution of the particles, g is the asymmetry parameter that describes the angular distribution of the scattered light, and $P(\theta)$ is the phase function, which describes the probability of light scattering at a particular angle.

D. *Image stabilization*

Because the water and things move when being photographed underwater, image stabilisation is a challenge. The Optical Flow Equation, a mathematical formula for image stabilization, defines how objects move inside an image and can be used to calculate the degree of motion blur. The Optical Flow Equation can be used to determine the degree of motion blur in underwater photographs and adjust for camera movement, according to a study by Harvey.[10]

$$I(x,y,t) = I(x+u,y+v,t+1) \quad (7)$$

where I is the image intensity, (x,y) are the spatial coordinates, t is the time, and (u,v) are the optical flow vectors that describe the motion of the objects in the image.

III. Existing Enhancement Methods for Underwater Images

A. *Wavelet-based denoising*

Wavelet-based denoising is a method that uses wavelet transform to decompose an image into different frequency components, denoise each component separately, and then reconstruct the image. The wavelet transform is a mathematical formula that breaks down a signal into its different frequency components, allowing for the analysis of the signal at different scales. The denoising process involves thresholding each frequency component to remove noise while preserving signal information. The threshold values can be determined using various techniques, such as the universal threshold, the Stein's Unbiased Risk Estimate (SURE), or the minimax threshold. In the end, the denoised frequency components are transformed using the inverse wavelet algorithm to reassemble the denoised image.

B. *Dark channel prior algorithm*

The DCP algorithm estimates the transmission map of the hazy image, which is a measure of the amount of haze at each pixel, and then uses it to recover the haze-free image. The transmission map is estimated by computing theminimum value of the dark channel over a local window centered at each pixel. This is expressed mathematically as:

$$DC(x)=\min\{\min\{I(y)\}: y\in\Omega(x)\} \quad (8)$$

where DC(x) is the dark channel value at pixel x, I(y) is the intensity value at pixel y, and $\Omega(x)$ is the set of pixels in a local window around pixel x. The transmission map is then computed as:

$$t(x) = 1 - w * DC(x) \quad (9)$$

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where w is a weight parameter that controls the strength of the haze removal. Finally, the haze-free image is recovered by applying a dehazing filter to the hazy image using the estimated transmission map. The DCP algorithm has been shown to be effective in removing haze and improving the visibility of underwater images.

C. Color Attenuation Prior algorithm

The Color Attenuation Prior (CAP) algorithm is a method for color correction in underwater images that uses the observation that the attenuation of color channels in water follows a particular pattern. The CAP algorithm estimates the color correction matrix that maps the observed color values to the true color values, based on the assumption that the attenuation of each color channel follows an exponential decay with depth. This is expressed mathematically as:

$$\text{I\_observed} = A * \text{I\_true} \tag{10}$$

whereI_observed is the observed color vector, I_true is the true color vector, and A is the color correction matrix that maps I_observed to I_true. The color correction matrix is estimated by minimizing the following objective function:

$$||\log(\text{I\_observed}) - \log(A * \text{I\_true})||^2 \tag{11}$$

subject to the constraint that A is a diagonal matrix with positive diagonal entries, to ensure that the attenuation of each color channel is modeled by an exponential decay. The solution to this optimization problem is given by:

$$A = \text{diag}(\exp(-b)) \tag{12}$$

where b is a vector of parameters that control the attenuation of each color channel. The CAP algorithm has been shown to be effective in correcting the color distortion in underwater images and improving the visibility of underwater scenes.[11]

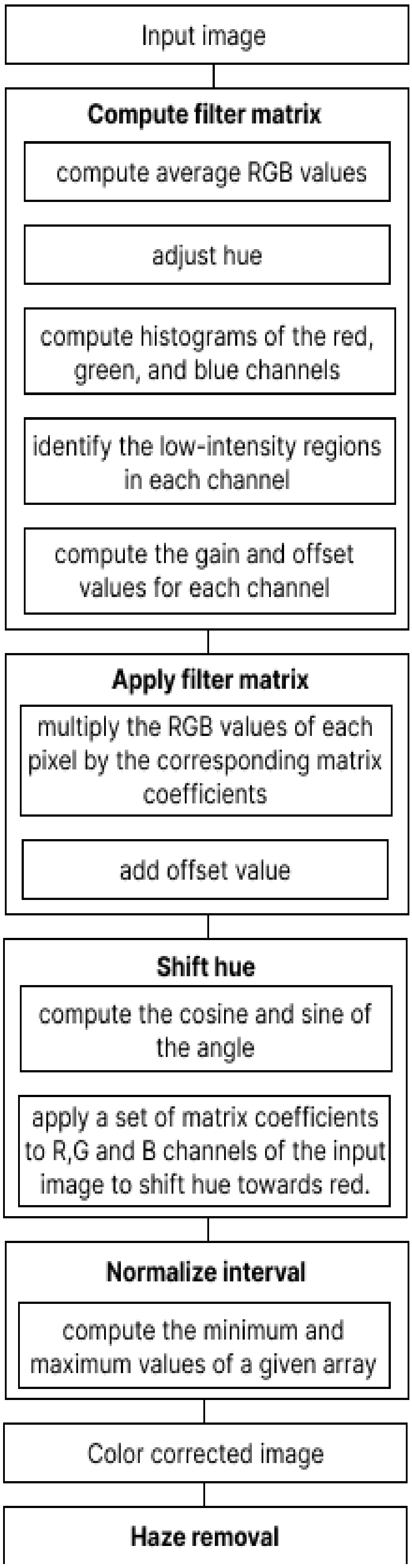
D. Retinex-based methods

Retinex-based algorithms can also be used for color constancy and correction by separating the reflectance and illumination components of an image. Multi-Scale Retinexwith Color Restoration (MSRCR) algorithm decomposes the input image into different scales, applies Retinex-based processing to each scale, and then combines the processed scales to obtain the final image. The mathematical equation for the MSRCR algorithm can be expressed as:

$$\text{I\_final}(x,y) = f(\lambda 1\text{I\_1}(x,y) + \lambda 2\text{I\_2}(x,y) + ... + \lambda n*\text{I\_n}(x,y)) \tag{13}$$

whereI_final(x,y) is the final image at pixel location (x,y), I_i(x,y) is the processed image at scale i, λi is the weight assigned to scale i, and f is a function that maps the weighted sum of the processed scales to the final image. The MSRCR algorithm has been shown to be effective in improving the color constancy and correction of underwater images, as well as enhancing the overall image quality.

IV. METHODOLOGY



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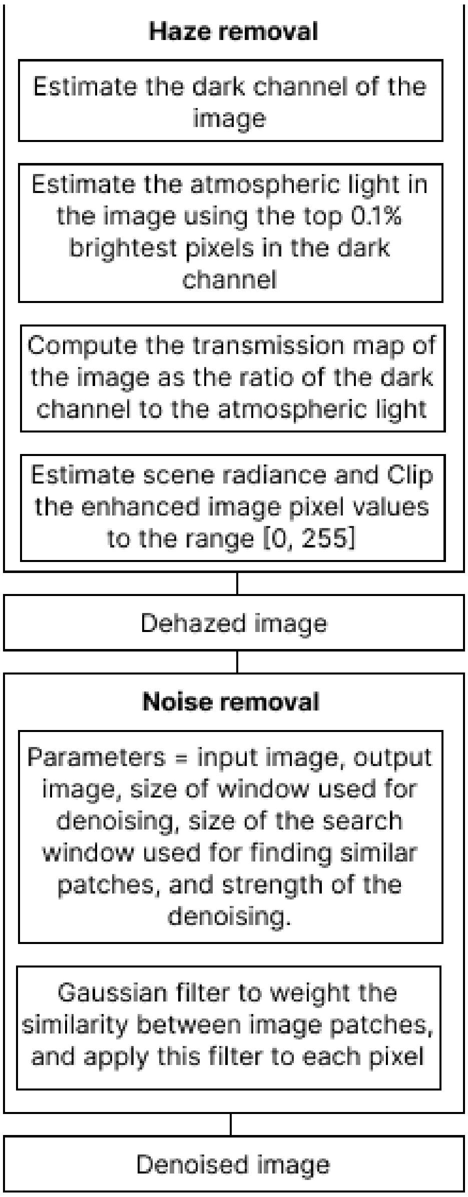

Fig. 1. Flow chart of the underwater image enhancement system.

The steps involved in the algorithm are as follows:

- Capturing and uploading the underwater image as an input to the system.
- Color correction is done by computing the filter matrix, applying the filtering matrix, shifting the hue and normalizing the interval.
- This is followed by dehazing the image using the dark channel prior algorithm.
- Denoising of the image is done using the fastNlMeansDenoisingColored() function in OpenCV which uses the parameters described in figure 1.
- This denoised image is the final image and can be used for object detection purposes.

V. Performance Evaluation

The performance evaluation for the proposed method can divided into two main areas-

1. Qualitative Analysis- The qualitative analysis of the proposed method is purely subjective as the enhanced images can only be observed by humans and the overall improvement purely depends on how a person perceives it. Therefore, it cannot be measured and represented, but everyone can make their own judgement about the same.
2. Quantitative Analysis- For quantitative analysis, 4 metrics have been used to compare the original image to the enhanced image.

A. Mean Square Error

It is a standard statistic for determining the quality of an image enhancement technique. It computes the average of the squared differences between the original and improved images. The formula for MSE is:

$$MSE = (1/N)^* \Sigma\, \Sigma\, [I(i,j) - K(i,j)]^2 \quad (14)$$

where I(i,j) is the pixel value of the original image at location (i,j), K(i,j) is the pixel value of the enhanced image at the same location, and N is the total number of pixels in the image.

B. Peak Signal-to-Noise Ratio

It is another another statistic widely employed to assess the quality of an image enhancement procedure. It calculates the ratio of the maximum potential signal value to the noise introduced by the picture enhancement method. PSNR is measured in decibels (dB). The formula for PSNR is:

$$PSNR = 10 * \log10((R\char`^2)/MSE)^2 \quad (15)$$

where R is the maximum possible pixel value of the image (for example, for an 8-bit grayscale image, R=255), and MSE is the mean squared error between the original and the enhanced images.

C. Structural Similarity Index

It works by comparing the structural information of the images, including luminance, contrast, and structure, to evaluate the similarity between them. It calculates the structural similarity of two images based on three factors: luminance, contrast, and structure. The SSIM mathematical equation is as follows:

$$SSIM(x, y) = [l(x, y)]^{\alpha}[c(x, y)]^{\beta}[s(x, y)]^{\gamma} \quad (16)$$

where x and y are the two images being compared, l(x,y), c(x, y), and s(x, y) are the local luminance, contrast, and structure similarities between x and y, respectively, and α, β, and γ are weighting parameters that determine the relative importance of the three factors.

As a rule, for all three metrics, the higher the values, the higher the enhanced image quality is, i.e., fewer differences between the original and enhanced image. Lower values indicate more differences which further indicate lower quality.

VI. Results And Discussion

Table below shows the quantitative results obtained after enhancing an image. The enhanced image obtained a MeanSquared Error value of 109.60, indicating that there is

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a considerable amount of difference between the noise and haze amounts in the original and enhanced image. The difference in the PSNR value between the original and enhanced image is 27.73 dB. In general, a PSNR value of 30 dB or more is considered good, therefore, there is scope of improvement in the proposed method. The Structural Similarity Index value obtained is 0.102, which means that both the images have a fair bit of difference in their structural information due to the removal of noise and haze as well as the color correction performed. Overall, the proposed method provides satisfactory results in enhancing underwater images.[12][13]

TABLE I.

Quantitative Analysis	**Metric**		
	MSE	***PNSR***	***SSIM***
Original	0	inf	-1
Enhanced	109.60	27.73	0.102

TABLE II.

Original	
Enhanced	

VII. Conclusion And Future Scope

In this paper, an approach for denoising underwater images using a combination filter to perform color correction, Single Image Haze Removal Using Dark Channel Prior (DCP), and Fast Denoising Colored Guided Image Filter is proposed. The proposed method effectively removes noise and enhances the contrast of the underwater images; however, the method can still further be optimised as can be seen from the low PSNR value obtained. The experimentalresults show that the proposed method can be applied to various underwater imaging applications, such as underwater surveillance, marine biology, and oceanography without using high computational energy and in a short amount of time.

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